Lisbon School of Economics & Management
Universidade de Lisboa

MASTERS IN FINANCE

MASTER´S FINAL WORK

DISSERTATION

HOW DOES PHYSICAL RISK IMPACT THE COST OF CAPITAL?

NICOLÒ GIOVANNI RIZZO

JULY 2024

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SUPERVISION:
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ABSTRACT

This study examines the impact of physical risk on the cost of capital for non-financial companies in the United States, using data from Moody's ESG-Physical Risk Management Score from 2021 to 2023. The results indicate a positive relationship between physical risk and both WACC and cost of equity capital, suggesting that higher physical risk increases these opportunity costs. Companies that manage physical risks better than their industry peers also benefit from lower capital costs, highlighting the importance of effectively managing this ESG related risk. The relationship between physical risk and the cost of debt is inconclusive, implying that lenders may emphasize other financial metrics over physical risk management. These findings highlight the need for companies to invest in robust physical risk mitigation strategies to optimize capital costs. The study contributes to the literature by extending the current understanding of sustainability risks with a focus on the consequences of physical risk management.

KEYWORDS: Cost of Capital; Climate Change, Climate Risk, Physical Risk; Sustainability

JEL: C51; F64; Q51; Q5

Resumo

Este estudo examina o impacto do risco físico no custo de capital para as empresas não financeiras nos Estados Unidos, utilizando dados do ESG-Physical Risk Management Score da Moody's de 2021 a 2023. Os resultados indicam uma relação positiva entre o risco físico e o WACC. e custo do capital próprio, sugerindo que um risco físico mais elevado aumenta estes custos de oportunidade. As empresas que gerem melhor os riscos físicos do que os seus pares do setor beneficiam também de custos de capital mais baixos, destacando a importância de gerir eficazmente este risco relacionado com o ESG. A relação entre o risco físico e o custo da dívida é inconclusiva, o que implica que os credores podem dar ênfase a outras métricas financeiras em detrimento da gestão do risco físico. Estas conclusões realçam a necessidade de as empresas investirem em estratégias robustas de mitigação de riscos físicos para otimizar os custos de capital. O estudo contribui para a literatura ao ampliar a compreensão atual dos riscos de sustentabilidade com foco nas consequências da gestão dos riscos físicos.

PALAVRAS-CHAVE: Custo de Capital; Alterações Climáticas; Risco Climático; Risco Físico; Sustentabilidade

JEL: C51; F64; Q51; Q5

GLOSSARY

ESG – Environmental, Social and Governance

COC – Cost of Capital

WACC – Weighted Average Cost of Capital

COE – Cost of Equity

COD – Cost of Debt

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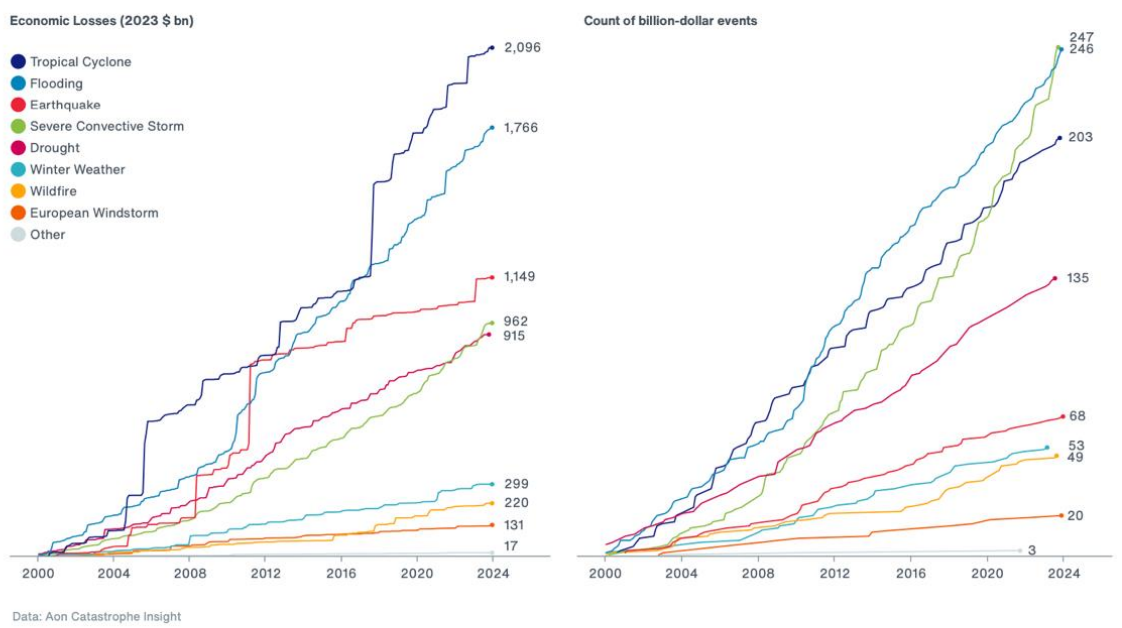
1. INTRODUCTION

Nowadays, it is increasingly common to approach finance and investment by focusing on managing risks arising from environmental factors, social issues, and corporate governance. In 2004 within the report "Who Cares Wins" (United Nations Global Compact) the term ESG-Environmental, Social and Governance, was introduced for the first time to describe all the above issues more succinctly.

Dwelling on the area related to the environment, climate change has become a major global concern that is having an influence on many different industries and economies all over the world. As can be observed in Figure I, (Climate and Catastrophe Insight Report 2024), the Economic Losses and the count of billion-dollar disasters, related to weather and climate events, increased significantly over the past years.

Figure I-Economic Losses and Billion-Dollar Disasters Trend



Source: Aon - Climate and Catastrophe Insight Report 2024

Given this rapidly growing trend in the last decade, more and more studies have been conducted to estimate the impact of these events on the economy. Matsumura, Prakash, and Vera-Munoz (2014) contributed with a study that demonstrated how increased carbon emissions lower business value. Carbon emissions raise downside risk and environmental concerns raise a company's cost of capital (Chava et al., 2011; Ilhan et al., 2020). Research indicates that stock markets do not effectively price climate risks, such as the growing likelihood of drought (Hong et al., 2019), conversely, in the Real Estate market, coastal residences that are susceptible to the risk of sea level rise are valued less (Bernstein et al., 2018).

Even in current investor relation reports, in the section “ITEM 1A: Risk Factors”, the attention to climate risks has become relevant, with particular attention for Transition risk and Physical risk.

Transition risk involves the economic and policy shifts associated with moving towards a low-carbon economy, including regulatory changes, technological advancements, and shifts in market preferences. Among the first to address transition risk, (Batten et al., 2016) noted that the returns of companies in the renewable energy sector are positively influenced by favourable news regarding transition risk. Similarly, Barnett et al. (2019) observed that the equity prices of companies more likely to be exposed to climate policy action are negatively influenced by transition risk. Furthermore, Capasso et al. (2020) and Barth et al. (2022) found that companies with higher greenhouse gas emissions, particularly due to CO2, and with lower environmental scores, have higher credit risks. These risks are measured by bond yield spreads and the distance to default.

Physical risk refers to the direct impacts of climate change, such as extreme weather events, rising sea levels, and temperature fluctuations, which can severely disrupt operations and damage assets (Batten et al., 2016; Dietz et al., 2016). While extensive research conducted on transition risks, as evidenced by the previous studies, showed more consistent results, we cannot affirm the same about physical risk. Conflicting findings are seen in US municipal bond pricing: some researchers discover discounts for vulnerability to sea level rise (Goldsmith-Pinkham et al., 2022), while others find no premium for climate risk (BlackRock Investment Institute, 2019). The data on the housing market is contradictory; some research (Bernstein et al., 2018; Ortega & Taspınar, 2016) indicate no price effect after Hurricane Sandy, while others show discounts for flood risk.

This paper aims to contribute to the literature by examining the link between physical risk management and the cost of capital. The cost of capital should be interpreted as the lowest return a company can earn to cover the expenses of a capital project. This is an assessment of whether the costs of the expected decision are reasonable. In this research, when referring to the cost of capital, it is done using the term WACC, weighted average cost of capital.

This study will focus on non-financial companies in the US market, using the ESG-Physical Risk Management score developed by Moody's to assess the impact of physical risk on the cost of capital. The Moody's score is a new metric designed to assess how well companies manage physical risks associated with climate change, providing a comprehensive view of their preparedness and resilience.

This study makes important contributions to the literature. It further supports the growing importance of physical risk and its management in corporate strategy. The impact of physical risk on the cost of capital and the cost of equity encourages managers to think beyond simple financial measures, as companies that manage physical risks better than their industry peers may also benefit from lower costs of capital. Finally, there is no evidence of the impact of physical risk on the cost of debt, implying that lenders may emphasize other financial metrics over physical risk management. From now on, when we talk about physical risk, we will always refer to physical risk management.

The rest of the document is organized as follows: Section 2 provides a review of the present literature, of how climate performance has been studied in relation to economic and corporate performance, from multiple points of view, concluding with the review of all studies implemented up to until now to measure the Physical Risk. The techniques and samples used are presented in Section 3. The results are discussed in Section 4. Conclusions, limitations, and directions for further research are finally presented in Section 5.

2. LITERATURE REVIEW

In recent years, companies and investors have paid more attention to understanding how environmental and physical hazards affect a company's cost of capital and, in turn, its overall health. This trend emphasizes how risk management and financial planning techniques must take climate change and related hazards into account. Although the idea of physical risk has become more popular recently, environmental issues and corporate health have been studied from multiple perspectives for many years.

2.1 Historical Perspective

Early research into the relationship between environmental performance and economic outcomes laid the groundwork for understanding these dynamics. For instance, Spicer (1978) conducted pioneering research indicating that pulp and paper companies with superior pollution control records tended to be more profitable. This study suggested that good environmental practices could correlate with better financial performance. However, Chen & Metcalf (1980) criticized Spicer's methodology, pointing out issues such as inappropriate statistical tests and a failure to control for firm size, which could have skewed the results. These critiques highlighted the need for more rigorous methodologies in studying the economic impacts of environmental performance.

During this period, many viewed corporate environmental initiatives as additional costs that companies should avoid. Mahapatra (1984) argued that investments in pollution management increased production costs and required more capital, perceiving these expenditures as resource outflows without financial benefits. This perspective dominated early thinking, framing environmental efforts as economically disadvantageous.

As research progressed, studies began to uncover positive correlations between environmental investments and economic performance. Hart, Ahuja (1996) and Nehrt (1996) found that investing in cleaner technologies led to abnormal profit growth, with early adopters reaping the greatest benefits. This research suggested that proactive environmental strategies could offer competitive advantages. Russo and Fouts (1997) expanded this notion by demonstrating a strong relationship between environmental and economic performance, especially in industries experiencing growth. Their work indicated that environmental initiatives could be particularly beneficial in dynamic market contexts.

Market-based measures further supported these findings. Klassen, McLaughlin (1996) and Fenn et al. (1997) , used market data to show that firms with better environmental performance often enjoyed higher market returns and valuations. These studies provided evidence that the market rewarded companies with strong environmental practices, reflecting investor recognition of the long-term benefits of sustainability.

2.2 Cost of Capital

Despite extensive research on the internal economic benefits of improved environmental performance, its impact on external factors like the cost of capital remained less explored. Feldman et al. (1997) observed positive effects on stock prices and beta from improvements in environmental risk management. Nevertheless, the lack of transparency in their proprietary model made it challenging for other researchers to confirm their findings. Recent research has questioned accepted theories, indicating that by lowering stock volatility and systematic risk, enhancing environmental performance might cut a firm's cost of capital. This perspective highlights the broader financial implications of good environmental management.

Ghoul et al. (2011) found that firms with higher corporate social responsibility (CSR) scores had significantly lower costs of equity capital, indicating that markets respond favourably to CSR initiatives. Their findings suggest that CSR activities can enhance a company's attractiveness to investors by mitigating perceived risks. Furthermore, Ghoul et al. (2018) extended this analysis internationally, showing that firms with strong corporate environmental responsibility (CER) practices enjoyed lower costs of capital globally. This study underscored the universal relevance of environmental responsibility in reducing financial risks.

Erragragui (2018) examined how creditors price firms' environmental, social, and governance (ESG) risks, finding that companies with higher ESG risks face higher borrowing costs. This research highlights the financial penalties imposed by creditors on firms that neglect ESG factors, emphasizing the importance of comprehensive risk management strategies. Garber and Hammitt (1998) provided further insights by showing how environmental liabilities, such as Superfund exposure, increased a firm's cost of capital. Their study focused on highly visible liabilities, which are easier for the market to understand compared to other environmental signals like Toxic Release Inventory reports. However, their research did not fully explore the broader implications of environmental risk management on the overall cost of capital, including debt financing and tax effects. This gap underscores the need for more comprehensive studies on how environmental risk management influences a firm's financial structure.

Heinkel et al. (2001) developed a theoretical model suggesting that exclusionary investment based on environmental performance could motivate firms to reduce pollution if the cost was lower than the equity disadvantage they would face. This model proposed that market pressures could drive environmental improvements. Sharfman et al. (2007) confirmed that better environmental risk management lowers the cost of capital by reducing future uncertainties and achieving tax benefits, using data from the Toxic Release Inventory. Their findings underscored the financial advantages of robust environmental practices.

2.3 Climate Change and Business Environment

Busch & Hoffmann (2011) highlighted that climate change causes systematic changes in the business environment for various reasons. First, as more nations tighten climate regulations, it becomes crucial for stakeholders and consumers to access low-carbon information. The increasing desire for accountability and openness in environmental activities is reflected in this trend. Second, rising production costs are a result of rising greenhouse gas emission prices and the expense of fossil fuels, which pushes companies to find more economical and ecologically friendly alternatives. Third, the growing global consciousness of climate change is propelling corporate endeavours towards the adoption of low-carbon management practices and renewable energy sources. These shifts represent a fundamental change in how businesses operate and react in response to climate challenges.

The effects of environmental performance on the financial market have been extensively studied recently. Chava et al. (2014) found that banks charge higher lending rates to firms with environmental concerns, indicating a risk premium associated with poor environmental practices. This finding suggests that lenders view environmental issues as a significant risk factor. Plumlee et al. (2015) found that the quality of voluntary environmental disclosures and future cash flows were positively correlated. According to this research, improved disclosures provide investors more knowledge and lessen information asymmetry, which raises company value and lowers equity costs.

Corporate social responsibility (CSR) activities have been shown to have a negative impact on the weighted average cost of capital (WACC) and the cost of debt, as indicated by Choi et al. (2010). They clarified that while investor preferences may result in poorer investment returns, corporations may more easily acquire money when they actively participate in CSR, which also lowers market risks. These studies suggest that CSR initiatives, while potentially costly, can enhance financial stability and investor confidence.

2.4 Broader Financial Implications

The wider financial ramifications of climate change encompass monetary policy and central banks. The impact of climate risks on central bank balance sheets and financial stability was examined by Batten et al. (2016) and Faccini et al. (2023) who advocated for the inclusion of climate concerns in monetary policy frameworks. According to their research, climate hazards may have an impact on financial regulatory and monetary policy choices. How investors see and respond to climate threats is a key factor in determining markets' performance. Businesses with greater carbon emissions have higher capital costs, according to research by Bolton and Kacperczyk (2021) and Goldsmith-Pinkham et al. (2022). This indicates a desire for compensation for carbon risk. According to this research, investors have been including climate risks more and more into their value models, especially following the 2015 Paris Agreement.

Engle et al. (2020) developed indices based on climate-related news coverage, showing that these indices can predict stock returns and capture investors' reactions to climate news. Meinerding et al. (2024) also found that climate-related news significantly influences market perceptions and investor behaviour. This research highlights the growing influence of climate information on financial markets.

2.5 Funding Sustainable Practices

The evolving landscape of climate finance highlights the growing importance of sustainable investing. Pástor et al. (2021; 2022) developed equilibrium models predicting that green assets, while generating lower expected returns compared to brown assets, can outperform when climate concerns rise unexpectedly. The increased knowledge of climate hazards among investors is reflected in this shift in investment preferences. According to Krueger et al. (2020), institutional investors may be especially aware of climate risks as they have a substantial impact on portfolio allocation and investment decisions. According to Li et al. (2020), companies that are exposed to greater climate risks modify their financial and capital structures appropriately. These studies demonstrate how the financial sector is becoming more and more focused on climate resilience and sustainability.

A fundamental framework for comprehending risk variables in stock and bond returns was developed by Fama and French (1993), who emphasized the significance of market, size, and value components. This approach has shown to be useful in assessing the ways in which various risks—including environmental risks—affect financial performance. Building on this, Fama and French (1997) analysed industry-specific costs of equity, providing insights into how industry characteristics and risks, including environmental factors, impact the cost of equity capital. These seminal works underscore the significance of incorporating various risk factors, including environmental risks, into financial models.

2.6 Physical Climate Risks

Physical climate risks, such as extreme weather events, rising sea levels, and temperature shocks, have significant economic impacts.

Specific sectors like agriculture could be studied if their geographic footprint was close to headquarters (Hong et al., 2019). Data vendors provided historical and forward-looking climate information to estimate exposure and assign scores to firms (Four Twenty-Seven, Ginglinger et al., 2023)

Researchers used textual analysis to examine the cross-section of expected returns, quantifying disclosures in annual reports to extract fundamental risks (Lopez-Lira et al., 2020). Kölbel et al. (2022) employed the BERT (Bidirectional Encoder Representations from Transformers) algorithm, to quantify the relative importance of climate risk words within the Item 1A Risk Factors section. This machine learning model excelled in natural language processing tasks, enabling the identification of context-specific terms related to climate risks. In a similar vein, Nagar & Schoenfeld (2022) focused on counting the occurrence of the word "weather" in different grammatical contexts within the 10-K filings. They distinguished between "weather" used as a noun, verb, and in weather-related contexts, offering a formula to calculate the exposure based on these counts. This method provided a nuanced understanding of how firms discussed weather-related risks in their filings. Zhang & Zhu (2020) extended this approach by creating binary and continuous variables to capture the presence and frequency of the term "weather" in 10-K filings. This method allowed for a more detailed statistical analysis of how often firms mentioned weather-related risks and in what context. Berkman et al. (2019) took a different approach by analysing the length and relevance of climate disclosures in Form 10-K using data from Ceres and CookESG. This method involved a comprehensive examination of the detailed sections provided in the filings, assessing the thoroughness and specificity of climate risk disclosures.

Quarterly earnings calls were another vital source of information. Sautner et al. (2020) used a bi-grams algorithm developed by King et al. (2017) to identify and analyse keywords related to climate risks in these calls. Bi-grams, which were pairs of consecutive words, helped in understanding the context and frequency of climate-related discussions during these quarterly updates. Similarly, Li et al. (2020) employed a pattern-based sequence recognition algorithm to detect climate risk-related keywords in earnings call transcripts. This method focused on identifying specific patterns and sequences of words, providing insights into how firms discussed climate risks in a more structured manner. McKnight & Linnenluecke (2019) explored daily press releases as a data source, analysing mentions of climate risks using Factiva's PR Newswire. This approach involved searching for keywords and phrases related to climate risks in press releases, assessing the frequency and context of these mentions to understand how firms communicated these risks publicly.

Surveys also played a crucial role in understanding firm-level climate risks. Schiemann & Sakhel (2019) collected physical risk submissions made to the Carbon Disclosure Project (CDP). These surveys provided detailed insights into firms' assessments of their climate risk exposure, including potential financial or strategic impacts. This voluntary disclosure by firms helped in understanding their perceived risks and readiness to tackle climate challenges. Khan et al. (2016) matched industry-specific guidance on materiality from the Sustainability Accounting Standards Board (SASB) to data from MSCI. This method leveraged SASB standards to determine material climate risks for different industries, correlating these with firm-level data to assess the actual impact.

Proprietary models offered advanced techniques for assessing climate risks. Schiemann & Hoepner (2020) utilized the eRevalue algorithm to identify and quantify environmental topics from firm filings. This advanced textual analysis method assessed the relevance and importance of climate risks mentioned in corporate disclosures, providing a sophisticated measure of environmental risk. The work of Four Twenty-Seven, as discussed in Gostlow et al. (2020), involved regressing returns on portfolios sorted by physical risk scores provided by the data vendor. This approach used historical and projected climate data to estimate physical risk exposure, assigning risk scores to firms and analysing their financial performance based on these scores. Similarly, Carbone 4 in Ginglinger et al. (2023) used a Climate Risk Impact Screening score to measure forward-looking climate risks. This model evaluated firms' exposure to future climate risks based on detailed climate projections and the firms' geographical footprint, offering a predictive measure of potential climate impacts.

Geographical data was critical for understanding how local climate conditions impacted firms. Griffin et al. (2019) geographically matched firms to extreme high surface temperature days, linking firms' locations to temperature data to assess the impact of extreme heat events on firm performance. Pankratz et al. (2019) regressed revenue and operating income of local firms on the number of extreme temperature days. This method analysed how temperature extremes affected the financial performance of firms with significant local exposure. Addoum et al. (2019) took a detailed approach by regressing establishment-level log of sales on average and extreme temperature exposure. This method involved analysing how temperature variations impacted sales at different firm establishments, providing a granular view of climate risk impacts. He found that high temperatures negatively impact firms' sales, productivity, and earnings, highlighting the direct economic consequences of climate change.

Kumar et al. (2013) regressed returns on abnormal US temperature changes, measuring exposure as absolute beta. This method assessed how temperature anomalies affected firm returns, using beta to capture systematic risk related to climate variations. Engle et al. (2020) analysed the impact of climate change news on firm returns by regressing returns on news articles from the Wall Street Journal. Their goal was to evaluate how news related to climate change influenced financial performance, using a comprehensive dataset of news articles and financial data.

Similarly, Hong et al. (2019) documented the substantial impact of droughts on food companies' stock returns, revealing the market's sensitivity to specific physical climate risks. These results emphasize how important it is for businesses to reduce and adapt to risks associated with climate change.

The impact of hurricanes and extreme weather unpredictability on financial markets were examined by Polacek (2018), who demonstrated that these occurrences significantly increase volatility and fluctuate asset prices. Their research highlights the market’s vulnerability to climate-related shocks. Painter (2020) demonstrated that physical climate risks like rising sea levels and extreme weather events significantly influence the pricing and yields of municipal bonds. These studies collectively underline the importance of incorporating physical climate risks into financial models and investment decisions.

The literature underscores the significant impact of physical climate risks on the economy. Climate change must be considered when making financial choices and creating regulatory frameworks because of the possible effects of these risks on investor behaviour, asset valuations, and corporate performance. It will be crucial to identify and lower these risks to maintain long-term financial stability and sustainable growth. According to recent studies, taking preventive measures to combat climate change can save capital expenses and yield significant financial rewards in addition to satisfying social and legal obligations. As climate change continues to pose economic challenges, businesses and investors must prioritize environmental performance to ensure long-term financial health and stability.

This article analyses the following research hypothesis:

Hypothesis 1: Better physical risk management is associated with lower cost of capital.

3. SAMPLE AND METHODOLOGY

3.1. Sample Construction

Through the application of three statistical models, the relationship between Physical risk and the cost of capital was analyzed. To do this the following databases were used: (a) Moody's Orbit provided physical risk management scores on the listed companies used in the model, from 2021 to 2023, (b) Refinitiv provided financial data for all calculated variables. Ordinary Least Squares (OLS) regressions were used for all three analyses. In the first model, the influence of changes in physical risk on WACC (weighted average cost of capital) was examined. The purpose is to determine how physical risk, together with other factors such as company size, leverage, asset tangibility and other control variables, can affect WACC. This analysis is crucial to better understand how the risks associated with climate change are reflected in companies' financing costs and, consequently, in their investment and strategic decisions. Then the relationship between Physical Risk and Cost of Capital was explored in depth, analyzing in detail the two factors that influence it. To do so, two other distinct statistical models were implemented, one for the Cost of Equity Capital and one for the Cost of Debt.

Since the physical risk management score is quite recent, the availability of data is limited, which is the reason why it was possible to study only the data for the years 2021 to 2023.

Considering that this paper aims to analyze physical risk, it was necessary to examine a market that is very influenced by this risk, the American market. In addition, all American companies, whose score is possible on Moody's, were selected, except for companies belonging to the financial sector, since their decisions on the capital market are strongly constrained by the specific regulation of the sector, fundamentally different from non-financial industries (Pittman & Fortin, 2004). Furthermore, companies with unavailable Physical Risk scores or insufficient data to calculate cost of capital parameters are also excluded from the sample. The sample is made up of 1430 companies, belonging to the United States of America and 10 industrial sectors, for a total of 2044 observations. The number of observations is not much greater than the number of companies, this is because, as previously mentioned, since the score is quite recent, it does not exist for all the companies examined, in the years under observation. The sample described above is the same used for all three models analyzed.

Appendix I presents the composition of the sample by sector. It is observed that the Healthcare, Technology, Industrials and Consumer Cyclicals sectors are the most represented sectors in the sample, with 21.82%, 21.33%, 14.53% and 13.55% respectively.

3.2. ESG-Physical Risk Management Score

Moody's ESG-Physical Risk Management Score was introduced as part of Moody's comprehensive framework for assessing environmental, social, and governance (ESG) risks. The score aims to evaluate how effectively companies manage the physical risks associated with climate change, such as floods, heat stress, hurricanes, sea-level rise, water stress, and wildfires. Developed to address the increasing need for robust climate risk assessment, the score leverages historical data and methodologies dating back to 2004, when Moody's began incorporating climate-related risk factors into their evaluations (Lafakis et al., 2022).

The ESG-Physical Risk Management Score ranges from 0 to 100, where higher scores indicate superior management of physical climate risks. Initially in this dissertation, it was examined another score, the Bloomberg Physical Risk score, which measures companies' exposure to physical climate risk. This score was subsequently not considered, as it only had one coefficient available, for each company, for the last 10 years and it was consequently not sufficient to delve deeper into the topic. The Bloomberg Physical risk score ranges from 0 to 100, where higher scores indicate greater exposure to physical risk and vice versa, so in other words where higher scores are negative. To continue with the same interpretation, the ESG-Physical Risk management score was multiplied by minus one, associating higher scores with a lower ability to manage physical risks and vice versa, and therefore where higher scores are negative. In the continuation of the work, the discussion of the results will always refer to the new and transformed ESG- Physical Risk score (Gonzalez, 2021).

The ESG-Physical Risk Management Score assesses companies based on three main criteria: leadership, implementation, and results. Leadership examines the company's strategy, governance, and target-setting for managing physical climate risks, focusing on the commitment and oversight provided by the company's leadership. Implementation evaluates the measures and systems a company has put in place to manage these risks, assessing their effectiveness and comprehensiveness. Results review performance trends and how the company handles controversies related to physical risks, utilizing key performance indicators (KPIs) to measure success. To ensure the assessments are tailored to the specific risks and standards of different industries, Moody's employs 40 sector-specific models. This approach accounts for the unique challenges and requirements of each industry, providing a nuanced and accurate evaluation (Lafakis et al., 2022).

The ESG-Physical Risk Management Score is integrated into broader economic models to assess potential impacts on GDP, productivity, and other macroeconomic variables. This involves adjusting GDP paths to reflect chronic physical risks as implied by various climate scenarios, such as those from the Intergovernmental Panel on Climate Change (IPCC). The economic impacts are assessed through several channels, including consumption (affected by loss of productive land due to sea-level rise), net exports (impacted by changes in tourism due to temperature increases), and productivity (influenced by heat stress and the spread of vector-borne diseases). Integrating sovereign climate risk scores into these economic models allows for dynamic adjustments and provides a comprehensive understanding of climate risks over time. This enhances the ability to predict and mitigate financial impacts of climate change, making it a vital tool for investors, regulators, and policymakers.

Moody's ESG-Physical Risk Management Score is a robust tool designed to measure how well companies manage physical climate risks. Introduced as part of Moody's efforts to address ESG and climate-related risks since around 2004, it provides valuable insights for assessing the financial stability and resilience of companies in the face of climate change. By focusing on comprehensive assessments and sector-specific models, Moody's offers a detailed view of how climate risks can impact financial stability and business performance.

3.3 Weighted Average Cost of Capital

3.3.1 Weighted Average Cost of Capital Measure

The Weighted Average Cost of Capital (WACC) is a financial metric used to calculate a company's cost of capital, where each category of capital is weighted proportionately. All sources of capital, including equity, preferred stock, and debt, are included in the calculation. Data for this measure was obtained from the Refinitiv database, which provides a comprehensive assessment of a company's total cost of capital. The WACC is fundamental in determining the minimum rate of return that a company must obtain to meet the expectations of its investors and financiers. A lower WACC implies that the company can finance its projects at a lower cost, making it more competitive.

3.3.2 Methodology

In order to study the relationship between WACC and physical risk taking into account firm-specific characteristics, year and industry impacts, three distinct models are used to evaluate research hypothesis 1, following the work of Gonçalves et al. (2022).

$$\text{WACC}_{i,t} = \beta_0 + \beta_1\text{Physical\_Risk}_{i,t} + \beta_2 Beta_{i,t} + \beta_3 Size_{i,t} + \beta_4 Lev_{i,t} + \beta_5 Tang_{i,t} + \beta_6 Perf_{i,t} + \beta_7 OCF_{i,t} + \beta_8 TobinQ_{i,t} + \beta_9 BTM_{i,t} + \beta_{10}\, Industry_i + \beta_{11} Year_t + \varepsilon_{i,t} \tag{1}$$

where *i* indicates each company and *t* the corresponding year. The physical risk management measure (*Physical_Risk*) serves as the first independent variable as well as the explanatory variable and is calculated as described in section 3.2. Company control variables are defined as follows:

Beta (*Beta*): Using data provided by Refinitiv, the levered beta is calculated over a five-year period with monthly data and measures the sensitivity of the company's return to the market. It includes both business risk (operational risk) and financial risk (capital structure risk). A higher beta indicates greater volatility and, therefore, higher risk, increasing the WACC. Beta is critical because it captures the company's overall exposure to systemic risks. A positive signal is expected on Beta.

Firm's size (*Size*): using data provided by Refinitiv, it is calculated as the natural logarithm of the market value of a company's share capital, in thousand euros. Larger companies tend to have a lower WACC due to greater stability and resources to address risks. However, size is not always significant because other variables can compensate for its influence.

Book-to-market ratio (*BTM*): it is the ratio between the book value of the capital and its market value. A higher BTM suggests that the company is undervalued, which could mean that it carries greater risk and, therefore, a higher WACC. According to Fama and French (1993), there is a positive correlation between the implicit cost of equity, cost of capital and book-to-market ratio because companies with higher book-to-market ratios are expected to generate returns ex higher posts than those with lower BTM.

Leverage (*Lev*): calculated as the ratio between total debt and total assets. Higher leverage indicates that the company uses more debt in financing its operations, which can increase the WACC due to additional interest costs and default risk. Leverage is important in the model because, together with beta, it captures the financial risks of the company.

Tobin Q (*TobinQ*): Measured as the sum of the market value of equity and total debt, divided by total assets. A higher Tobin Q, i.e. above 1, indicates that the market values the company more than the book value of its assets, suggesting growth expectations and potentially reducing the WACC.

Performance (*Perf*): Measured as the ratio of income before extraordinary items to sales. It indicates the operational efficiency of the company. High performance usually reduces the WACC as investors view the company as more stable and profitable.

Tangibility (*Tang*): Ratio of property, plant and equipment to total assets. Greater tangibility means the company has more physical assets that can be used as collateral for debt, potentially reducing the WACC.

Operating Cash Flow (*OCF*): Ratio of operating cash flow to total assets. It indicates the company's ability to generate cash from core operations, a measure of financial stability. Higher Operating Cash Flow usually reduces WACC.

Finally, dummy variables are used to control for industry membership and years. These variables are calculated using the computer language STATA and are based on the observation that different sectors present different levels of perceived risk to lenders. In Appendix II, each variable is explained along with the corresponding calculation formula.

To study in more detail how companies manage physical risk, they were compared with their industry, using the variable *IndDev*, employed in Equation 2. *IndDev* calculated as the difference between the company's physical risk score and the industry median. This variable measures how much a company's physical risk deviates from the average of its sector and therefore what is the deviation of the individual physical risk compared to the sector average, per year. Both the social and financial benefits are substantial only when compared to those of companies operating in similar economic conditions because companies in the same sector are subject to identical rules and have similar access to sources of capital and investment opportunities. A negative IndDev value indicates that the company is more efficient at managing physical risk than the industry average, which should reduce the WACC.

(2)
$$\mathrm{WACC}_{i,t} = \beta_0 + \beta_1 \mathrm{Physical\_Risk}_{i,t} + \beta_2 IndDev_{i,t} + \beta_3 Beta_{i,t} + \beta_4 Size_{i,t} + \beta_5 \mathrm{BTM}_{i,t} + \beta_6 \mathrm{Lev}_{i,t} + \beta_7 \mathrm{TobinQ}_{i,t} + \beta_8 \mathrm{Perf}_{i,t} + \beta_9 \mathrm{Tang}_{i,t} + \beta_{10} OCF_{i,t} + \beta_{11} Industry_i + \beta_{12} Year_t + \varepsilon_{i,\mathrm{t}}$$

To determine whether the magnitude of the deviation has an impact on the relationship, equation 3 attempts to investigate this deviation in more detail. The square of IndDev, or SqrDev, is added to the model. By squaring the deviation of physical risk from the industry median, we can examine in more depth whether companies have better risk management.

(3)
$$\mathrm{WACC}_{i,t} = \beta_0 + \beta_1 \mathrm{Physical\_Risk}_{i,t} + \beta_2 IndDev_{i,t} + \beta_3 SqrDev_{i,t} + \beta_4 Beta_{i,t} + \beta_5 Size_{i,t} + \beta_6 BTM_{i,t} + \beta_7 \mathrm{Lev}_{i,t} + \beta_8 \mathrm{TobinQ}_{i,t} + \beta_9 \mathrm{Perf}_{i,t} + \beta_{10} \mathrm{Tang}_{i,t} + \beta_{11} OCF_{i,t} + \beta_{12} Industry_i + \beta_{13} Year_t + \varepsilon_{i,\mathrm{t}}$$

3.4 Cost of Equity

3.4.1 Cost of Equity Measure

As explained previously, to analyse the relationship between physical risk and cost of capital a WACC model and its determinants are included. Specifically, the cost of equity and cost of debt are also used.

The cost of equity represents the theoretical return a company pays to its equity investors. It is calculated by multiplying the market risk premium by the security's beta, plus an inflation-adjusted risk-free rate. The equity risk premium is equal to the expected market return minus the inflation-adjusted risk-free rate. This measure is crucial to understanding the return required by equity investors to offset the risk associated with investing in the company. Data for the cost of equity capital was obtained from the Refinitiv database, which provides an accurate estimate of the return required by investors.

3.4.2 Methodology

In terms of company-specific control variables, a part of the variables calculated before for the WACC, i.e. the market beta, the size, the book-to-market ratio, the financial leverage (calculated differently compared to the previous model), the year and industry effects were used, in accordance with Gonçalves et al. (2022) and Ghoul et al. (2011). The following model is used to continue investigating research hypothesis 1:

(4)

$$COE_{i,t} = \beta_0 + \beta_1 \text{Physical\_Risk}_{i,t} + \beta_2 Beta_{i,t} + \beta_3 Size_{i,t} + \beta_4 BTM_{i,t} + \beta_5 \text{Lev}_{i,t} + \beta_6 Industry_i + \beta_7 Year_t + \varepsilon_{i,t}$$

where *i* indicates each company and *t* the corresponding year. The physical risk management measure (*Physical_Risk*) serves as the first independent variable as well as the explanatory variable and is calculated as described in section 3.2. Company control variables are defined as follows:

Beta (*Beta*): Using data provided by Refinitiv as before, leveraged beta is calculated over a five-year period with monthly data. The Capital Asset Pricing Model (CAPM) states that the cost of equity and beta should be positively correlated.

Firm’s size (*Size*): using data provided by Refinitiv, it is calculated as the natural logarithm of the market value of a company's share capital, in thousands of euros.

Book-to-market ratio (*BTM*): it is the ratio between the book value of the capital and its market value.

Leverage (*Lev*): is the ratio of total debt to equity market value.Fama and French (1993) emphasized how companies with higher levels of debt achieve larger stock returns in the future. Consequently, a favorable correlation is anticipated.

Because Eugene Fama et al (1997) found that there is significant variation in factor loadings across industries, year and industry controls are included in all regressions in addition to firm-specific controls.

Subsequently, the same changes as in paragraph 3.3.2 were made to equation (4), with the addition of IndDev and SqrDev. In Appendix III, each variable is explained together with the corresponding calculation formula.

3.5 Cost of Debt

3.5.1 Cost of Debt Measure

The cost of debt represents the marginal cost to the firm of issuing new debt at the current time. It is calculated by adding the weighted cost of short-term debt and the weighted cost of long-term debt, based on the 1-year and 10-year points of an appropriate credit curve. This measure reflects the actual cost of debt to the company, considering market conditions and the company's risk profile. Cost of debt data was obtained from the Refinitiv database, which provides a detailed analysis of short- and long-term financing costs.

3.5.2 Methodology

In order to address research hypothesis 1, three distinct models are used to explore potential correlations between cost of debt and physical risk, while controlling for firm-specific characteristics, as well as year and sector effects, following La Rosa et al. (2018)

$$\textbf{(5)} \quad COD_{i,t} = \beta_0 + \beta_1 \text{Physical\_Risk}_{i,t} + \beta_2 Beta_{i,t} + \beta_3 Size_{i,t} + \beta_4 Lev_{i,t} + \beta_5 TobinQ_{i,t} + \beta_6 Perf_{i,t} + \beta_7 \text{Tang}_{i,t} + \beta_8 OCF_{i,t} + \beta_9 Industry_i + \beta_{10} Year_t + \varepsilon_{i,t}$$

where *i* denotes each company and *t* the corresponding year. The physical risk management measure (*Physical_Risk*) serves as the first independent variable and is computed as described in section 3.2. Firm control variables are the same ones used in the WACC model, excluding the BTM, and are calculated in the same way. Below is the list of variables: Beta, Firm's size, Leverage, Tobin Q, Performance, Tangibility and Operational Cost of Capital.

Following the structure of the previous two models, also in this case IndDev and SqrDev were added to the equations for a robustness test. In Appendix IV, each variable is explained along with the corresponding calculation formula.

4. RESULTS

4.1 Descriptive Statistics

Table I provides descriptive data of the variables considered in the three models (WACC, cost of equity and cost of debt). The choice to use a single descriptive table to represent three distinct models is justified by the consistency of the independent variables used.

TABLE I SAMPLE DESCRIPTIVE STATISTICS

	Obs.	Mean	Median	Standard Deviation	Q1	Q3
WACC	2044	0.0360	0.0183	0.0339	0.0152	0.0579
Cost of Equity	2044	0.0380	0.0151	0.0390	0.0151	0.0667
Cost of Debt	2044	0.0345	0.0243	0.3675	0.0149	0.0409
Physical Risk	2044	87.6179	94.0000	14.8046	78.0000	100.0000
Beta	2044	1.1640	1.1035	0.6379	0.7565	1.5035
Size	2044	21.5677	21.9513	2.6393	19.8270	23.4936
Book to Market	2044	0.3718	0.2694	0.3920	0.1075	0.5322
Leverage	2044	0.0003	0.0003	0.0002	0.0001	0.0004
Tobin Q	2044	2.8133	1.3936	4.5499	0.7245	2.9443
Performance	2044	-1.8451	0.0439	10.7849	-0.0569	0.1368
Tangibility	2044	0.2581	0.1428	0.2689	0.0560	0.3916
Operating Cashflow	2044	0.0056	0.0613	0.2232	-0.0168	0.1145

The variables show significant differences between companies in terms of risk and performance, for example, the average beta is 1.1640, indicating some exposure to market risk, while the average company size is 21.5677, with moderate variability. The average book to market ratio is 0.3718, reflecting a different market valuation. The average performance is negative, indicating that many companies have recorded losses. Physical Risk has an average of 87.6179, suggesting variable physical risk management capabilities across companies. In summary, differences in key variables suggest that companies adopt different financial strategies. The consolidated table offers a unified view of the statistical characteristics, facilitating the comparison and understanding of the different company performance measures.

4.2 Correlation Matrix

The correlation matrix in Appendix V of the document analyses the relationships between the independent variables used in the WACC, Cost of Equity and Cost of Debt models. Using a single matrix simplifies comparative analysis due to the consistency of the variables. The WACC shows a strong positive correlation with the cost of equity capital (coefficient 0.876), suggesting that companies with a high cost of equity tend to have a high WACC. Physical risk, calculated on a scale of 0 to 100, has a negative correlation with company size (coefficient -0.295), indicating that larger companies manage physical risk better. Beta is positively correlated with the cost of equity capital (coefficient 0.203), reflecting that greater systematic risk leads to a higher cost of equity capital. Company size shows positive correlations with tangibility (coefficient 0.261) and operating cash flow (coefficient 0.580), suggesting that larger companies tend to have more tangible assets and stable operating cash flows. Operating cash flow is positively correlated with Tobin Q (coefficient 0.378), indicating that better operating cash flow is associated with higher market value. In summary, the correlation matrix provides a detailed view of the relationships between the variables, facilitating the understanding of the dynamics that influence the WACC, the cost of equity and the cost of debt in the analysed companies.

4.3 Weighted Average Cost of Capital - Model Results

Table II reports the results of the regressions estimated using the ordinary least squares (OLS) method on a combined sample. In all models, WACC (Weighted Average Cost of Capital) serves as the dependent variable. Several physical risk metrics are included as explanatory variables, and each model specification includes ten firm-specific control variables, as well as year and industry effects.

TABLE II WEIGHTED AVERAGE COST OF CAPITAL REGRESSION MODEL RESULTS

Variables	(1)	(2)	(3)
Physical Risk	0.015*	0.049***	0.047***
	(0.008)	(0.010)	(0.011)
IndDev		-0.034**	-0.035***
		(0.014)	(0.013)
SqrDev			-0.000
			(0.000)
Beta	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)
Size	-0.003	-0.003	-0.002
	(0.002)	(0.002)	(0.002)
Book to Market	0.002	0.002	0.003
	(0.002)	(0.002)	(0.002)
Leverage	6.219**	6.219**	6.205**
	(2.495)	(2.495)	(2.493)
TobinQ	-0.002*	-0.002*	-0.001
	(0.001)	(0.001)	(0.001)
Performance	0.002	0.002	0.002
	(0.006)	(0.006)	(0.006)
Tangibility	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)
Operating Cash Flow	-0.001	-0.001	-0.001
	(0.007)	(0.007)	(0.006)
Intercept	0.048***	0.016	0.018*
	(0.014)	(0.010)	(0.009)
Years	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Observations	2044	2044	2044
Adj R^2	0.587	0.587	0.587
F-stat	337.915	337.915	322.590

**** p<.01, ** p<.05, * p<.1*, respectively (1), (2) and (3) – Pooled OLS.
Robust standard errors are in parentheses.
All variables are defined in Appendix II.

Model (1) highlights a significant positive correlation of 10% between Physical Risk and WACC, suggesting that companies with a lower physical risk management capacity face a higher cost of capital. This result is consistent with the idea that high exposure to physical risks increases investors' risk perception, which therefore requires a higher return. Specifically, the coefficient of Physical Risk is positive and significant, indicating that an increase in the physical risk score translates into an increase in WACC.

Model (2) introduces the variable IndDev, which measures the deviation of physical risk from the industry median per year. Here, the variable IndDev shows a negative and significant coefficient, suggesting that companies that manage physical risk better than the industry average tend to benefit from a lower WACC. This finding highlights the importance of effective physical risk management. The presence of IndDev in the model makes the Physical Risk coefficient even more significant, reinforcing the idea that physical risk management is crucial to optimize the cost of capital.

In model (3) the variable SqrDev, the square of IndDev, is added to capture any non-linear effects. However, SqrDev is not found to be significant, suggesting that the magnitude of physical risk deviation from the industry median has no additional impact on WACC beyond that already captured by IndDev. This result implies that it is not the extreme deviations that matter, but rather the ability to keep physical risk below the industry average.

Control variables, such as Beta, Size, Leverage and TobinQ, show results consistent with existing literature. Beta is positive and highly significant in all models, confirming that higher market risk increases WACC. This is in line with financial theory, which suggests that investors require a higher return to compensate for high systematic risk. Size, however, is not significant, indicating that the size of the company does not have a clear impact on the WACC in the sample considered.

Leverage shows a positive and significant coefficient, indicating that higher debt increases WACC. This result is consistent with the theory that a high level of debt is associated with greater financial risk, which leads to an increase in the cost of capital. Similarly, the variable Tobin Q shows a negative and significant relationship with WACC, suggesting that firms valued more than the book value of their assets tend to have a lower WACC. This can be interpreted as a positive signal from the market regarding the company's ability to grow in the future.

The other control variables, such as Performance, Tangibility, Operating Cash Flow and Book to Market, do not show consistent significance in the models, indicating a less significant impact on WACC. In particular, the lack of significance for Tangibility suggests that, in the context of the sample considered, the presence of tangible assets does not significantly influence the cost of capital. Similarly, Operational Performance and Operational Cash Flow do not appear to have a decisive effect on WACC.

In summary, the regression results clearly indicate that physical risk management is crucial for reducing companies' cost of capital. Companies that manage physical risks better than the industry average (negative IndDev) tend to have a lower WACC, highlighting the importance of effective risk management. Control variables such as Beta and Leverage show a significant impact on WACC, strengthening the robustness of the model. The non-significance of variables such as Size and SqrDev suggests that other factors, such as physical risk and leverage, are more influential in determining WACC. These results offer a solid basis for understanding the dynamics that influence the cost of capital in the companies considered and highlight the importance of risk management integrated into corporate strategies.

4.4 Cost of Equity - Model Results

Table III reports the main results of the regressions estimated using the ordinary least squares (OLS) method on the sample of companies. In all models, the dependent variable is the Cost of Equity (COE). Key explanatory variables include several physical risk indicators, while each model specification includes six firm-specific control variables, as well as year and industry effects.

Model (1) explores the association between physical risk management performance and the implicit cost of equity capital. The Physical Risk variable shows a positive and significant coefficient, indicating that an increase in physical risk is associated with an increase in COE. This suggests that companies with greater vulnerability to physical risks face higher costs of capital, as investors perceive these companies as riskier. The control variable Beta is positive and highly significant, consistent with the findings of Hail and Leuz (2006), indicating that greater systematic risk increases the cost of equity capital. Size shows a positive and significant coefficient, suggesting that, in this sample, larger firms pay higher equity premiums, a result at odds with existing literature (Ghoul et al., 2011). This can be attributed to the sample selection, which was limited to large companies.

TABLE III COST OF EQUITY REGRESSION MODEL RESULTS

Variables	(1)	(2)	(3)
Physical Risk	0.016*	0.042***	0.040***
	(0.008)	(0.012)	(0.012)
IndDev		-0.026**	-0.027**
		(0.013)	(0.012)
SqrDev			-0.000
			(0.000)
Beta	0.011***	0.011***	0.011***
	(0.002)	(0.002)	(0.001)
Size	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
Book to Market	0.003*	0.003*	0.003*
	(0.002)	(0.002)	(0.002)
Leverage	2.416***	2.416***	2.454***
	(0.688)	(0.688)	(0.670)
Intercept	0.051**	0.026	0.028
	(0.021)	(0.020)	(0.018)
Years	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Observations	2044	2044	2044
Adj R^2	0.724	0.724	0.724
F-stat	586.835	586.835	549.488

**** p<.01, ** p<.05, * p<.1,* respectively (1), (2) and (3) – Pooled OLS.
Robust standard errors are in parentheses.
All variables are defined in Appendix III.

Model (2) introduces the variable IndDev, which measures the deviation of physical risk from the industry median per year. The coefficient of IndDev is positive and significant, suggesting that negative deviations from the industry median (i.e. better than average physical risk management) are viewed positively by investors, who demand lower equity premiums. In other words, when a company manages physical risk better than the industry average, its cost of equity falls. Conversely, when physical risk management is worse than the industry average, the cost of equity capital increases. This model reinforces the idea that investors reward companies that invest in effective physical risk management.

Model (3) adds the variable SqrDev, the square of IndDev, to capture any non-linear effects of deviations from the average sector risk. Although the coefficient of SqrDev is positive, it is not statistically significant, indicating that there is insufficient evidence to conclude that extreme deviations (both positive and negative) from industry average physical risk have a significant impact on COE.

Regarding the control variables, all models report a positive and significant coefficient for Beta, consistent with the literature suggesting that greater market risk increases COE. The Leverage variable has a positive and significant coefficient, indicating that higher debt is associated with an increase in COE, reflecting the financial risk perceived by shareholders. The BTM (Book to Market ratio) variable shows a positive and significant coefficient in all models, suggesting that investors demand higher equity premiums for companies with fewer growth opportunities. Size, as mentioned, shows a positive and significant coefficient, implying that larger firms in the sample tend to pay higher equity premiums. This result may be influenced by the sample selection, limited to large companies.

In summary, the regression results clearly indicate that physical risk management is a crucial factor in determining the cost of equity capital. Companies that manage physical risks better than the industry average tend to have a lower cost of equity, highlighting the importance of effective physical risk management. The control variables, such as Beta and Leverage, show a significant impact on the cost of equity, confirming the robustness of the model. The non-significance of SqrDev suggests that it is not extreme deviations that influence cost of equity, but rather the ability to keep physical risk below the industry average. These results offer a solid basis for understanding the dynamics that influence the cost of equity capital in the companies considered, underlining the importance of risk management integrated into corporate strategies.

4.5 Cost of Debt - Model Results

Table IV reports the results of the regressions estimated using the ordinary least squares (OLS) method on a combined sample. In all models, the dependent variable is the Cost of Debt (COD).

TABLE IV COST OF DEBT REGRESSION MODEL RESULTS

Variables	(1)	(2)	(3)
Physical Risk	0.034	0.144**	0.172**
	(0.029)	(0.062)	(0.085)
IndDev		-0.111**	-0.091**
		(0.045)	(0.040)
SqrDev			0.003
			(0.003)
Beta	0.008	0.008	0.009
	(0.006)	(0.006)	(0.006)
Size	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)
Leverage	92.879	92.879	93.141
	(59.192)	(59.192)	(59.442)
TobinQ	-0.001	-0.001	-0.002
	(0.001)	(0.001)	(0.001)
Performance	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Tangibility	-0.014	-0.014	-0.013
	(0.024)	(0.024)	(0.024)
Operating Cash Flow	-0.160	-0.160	-0.158
	(0.155)	(0.155)	(0.153)
Intercept	0.028	-0.076**	-0.096**
	(0.024)	(0.037)	(0.045)
Years	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Observations	2044	2044	2044
Adj R^2	0.010	0.010	0.010
F-stat	10.184	10.184	9.316

**** p<.01, ** p<.05, * p<.1*, respectively (1), (2) and (3) – Pooled OLS.
Robust standard errors are in parentheses.
All variables are defined in Appendix IV.

Model (1) explores the association between physical risk and the implicit cost of debt. The Physical Risk variable shows a positive, but not significant, coefficient, suggesting that physical risk does not have a significant impact on cost of debt in this model. However, it is interesting to note that the coefficient of Leverage is significant and positive, indicating that higher leverage is associated with an increase in cost of debt. This result is consistent with the theory that a high level of debt is perceived as riskier by creditors, leading to an increase in the cost of debt. Tangibility shows a negative and significant coefficient, suggesting that higher asset tangibility reduces cost of debt, since tangible assets can be used as collateral, reducing the risk for creditors.

Model (2) introduces the variable IndDev, which measures the deviation of physical risk from the industry median per year. Here, IndDev shows a negative and significant coefficient, suggesting that companies that manage physical risk better than the industry average tend to benefit from lower COD. This finding highlights the importance of effective physical risk management. Furthermore, the coefficient of Physical Risk becomes positive and significant in this model, indicating that an increase in physical risk is associated with an increase in COD. This reinforces the idea that companies with greater vulnerability to physical risks are perceived as riskier by creditors.

Model (3) adds the variable SqrDev, whose coefficient is positive and significant, suggesting that there are nonlinear effects in how deviations from the average industry risk affect COD. This result implies that extreme deviations (both positive and negative) from the industry average physical risk can increase COD. Meanwhile, the coefficient of Physical Risk remains positive and significant, confirming that high physical risk is associated with a higher cost of debt.

Regarding the control variables, the results show that Beta is not significant in any of the models, which indicates that systematic market risk does not significantly affect the cost of debt (COD) of companies in the analysed sample. However, leverage is consistently positive and significant in all models, indicating that higher leverage leads to an increase in COD, reflecting the additional risk perceived by creditors. Asset tangibility shows a negative and significant coefficient, suggesting that higher tangibility reduces COD, since tangible assets can be used as collateral, decreasing the risk for creditors. Operating performance and the ability to generate operating cash flows, measured by the Performance and OCF variables respectively, do not significantly influence COD.

Moving on to the analysis of the model statistics, the F-statistic tests the hypothesis that all regression coefficients are equal to zero and is significant in all models, indicating that at least one of the independent variables has a significant effect on COD. Log-likelihood measures the log-likelihood of the model, and although higher values indicate a better model, the results suggest that there is room for improvement in model specification.

In terms of the economic significance of the variables, companies with less effective management of physical risks face higher debt costs. This is crucial for creditors, as increased vulnerability increases the risk of default. For debtholders, physical risk is a critical aspect to evaluate as a company with high vulnerability to physical risks may be more likely to fail or face financial difficulties. The higher cost of debt for companies with high physical risk scores reflects this concern. An increase in the cost of debt impacts the Weighted Average Cost of Capital (WACC), making overall financing more expensive and potentially reducing the company's ability to grow and invest. Lenders demand higher interest rates to compensate for the additional risk, which in turn increases the company's cost of capital.

In conclusion, the analysis demonstrates that physical risk management is crucial in determining the cost of debt. Companies that better manage these risks enjoy lower debt costs, benefiting from a lower WACC and greater growth opportunities. The findings suggest that lenders are particularly attentive to companies' ability to manage physical risks, and this is reflected in the interest rates charged.

4.6 Robustness Tests

To ensure the robustness of the results, further regression analyses were performed excluding the Physical Risk variable and focusing exclusively on IndDev and, subsequently, on SqrDev, together with control variables, sector and year fixed effects. This approach helps to verify whether the relationships observed in previous models hold even when some key variables are excluded, thus strengthening the credibility of our results. In this robustness test, the impact of IndDev on the three dependent variables of the model was analysed: the weighted average cost of capital, the cost of equity and the cost of debt. The results are summarized in the following table.

The coefficient of IndDev in the WACC model is 0.015 (significant at the 10% level), suggesting a positive relationship between deviation from the industry median and WACC. This indicates that companies with a higher IndDev, representing higher physical risk than the industry average, tend to have a higher WACC. This can be interpreted as the market perceiving greater risk in these companies, demanding a higher return to compensate for that risk, consistent with existing literature (Ghoul et al., 2011).

TABLE V ROBUSTNESS TESTS EXPLORING THE RELATIONSHIP BETWEEN INDDEV AND COST OF CAPITAL COMPONENTS

Variables	WACC	COE	COD
IndDev	0.015*	0.016*	0.034
	(0.008)	(0.008)	(0.029)
Firm-controls	Yes	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Observations	2044	2044	2044
Adj R^2	0.587	0.724	0.010
F-stat	337.915	586.835	10.184

**** p<.01, ** p<.05, * p<.1. Robust standard errors are in parentheses.* All variables are defined in Appendix II, III, IV.

Similarly, the COE model reports a coefficient of 0.016 for IndDev, which is also significant at the 10% level. This reinforces the idea that deviations from industry norms in physical risk management are perceived as risky by equity investors, who therefore demand higher returns. This finding is in line with literature suggesting that equity investors are particularly sensitive to performance relative to industry standards, as it may reflect management efficiency and future risk (Sharfman et al., 2007).

For the COD model, the IndDev coefficient is positive (0.034) but not statistically significant. This lack of significance suggests that lenders may not penalize deviations from industry physical risk management norms as heavily as equity investors do, as lenders place greater emphasis on other financial metrics and collateral such as collateral and historical performance rather than on physical risk management.

Also in the second robustness set, it was examined the relationship between the dependent variables examined before, the WACC, the cost of equity and the cost of debt, but with the SqrDev, instead of the IndDev. The SqrDev variable represents the square of the company's physical risk deviation from the industry median, providing a more sensitive measure of extreme deviations from the industry average.

From the regression results, it is observed that SqrDev does not have a significant impact on WACC and COE, while it shows a non-significant positive relationship with COD. These results suggest that extreme deviations in physical risk, whether positive or negative, do not significantly influence firms' cost of capital and cost of debt distinctly and therefore do not influence the cost of equity capital required by investors. However, the control variables generally show expected and significant signs, confirming the robustness of the models. In particular, leverage continues to show a positive and significant impact on COD, reflecting the greater risk perceived by creditors in the presence of high debt.

TABLE VI ROBUSTNESS TESTS EXPLORING THE RELATIONSHIP BETWEEN SQRDEV AND COST OF CAPITAL COMPONENTS

Variables	WACC	COE	COD
SqrDev	-0.001	-0.001	0.001
	(0.000)	(0.000)	(0.001)
Firm-controls	Yes	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Observations	2044	2044	2044
Adj R^2	0.586	0.723	0.010
F-stat	336.316	578.334	10.380

**** p<.01, ** p<.05, * p<.1. Robust standard errors are in parentheses.* All variables are defined in Appendix II, III, IV.

Robustness tests conducted on the models highlight the importance of physical risk management relative to the industry average (IndDev) on the cost of capital. The positive relationship between IndDev and both WACC and COE indicates that deviations from industry norms, represented by above-average physical risk, are perceived negatively by investors. These findings suggest that investors see such deviations as signals of potential inefficiencies and additional risk, thus increasing the costs of equity and overall capital for companies. As a result, maintaining physical risk management practices in line with industry norms is crucial for companies to effectively manage their capital costs. This type of analysis also allows you to isolate the impact of relative physical risk management, reducing the potential for multicollinearity and ensuring that results are not confused with those of Physical Risk.

By excluding Physical Risk from the models, the results show that IndDev effectively captures how the company manages physical risk relative to its direct competitors, providing a crucial perspective for understanding competitive positioning. This helps to identify whether it is deviation from industry norms that is driving cost implications rather than absolute levels of physical risk management. From a strategic perspective, companies can use these insights to align their physical risk management approaches more closely with industry standards, thereby potentially reducing their capital costs. On the other hand, analyses performed with SqrDev, which represents extreme deviations from the average industry risk, do not show a significant impact on the cost of capital components. This implies that while investors and creditors consider a company's positioning relative to the industry average to be relevant, extreme deviations from the average risk are not a significant driver of the cost of capital.

In summary, robustness tests confirm that physical risk management is a key determinant of the cost of capital. Companies need to pay particular attention to how their physical risk compares to the industry average, as deviations can significantly affect their costs of capital. These findings provide companies with valuable insights into how their physical risk management is perceived by financial markets, helping them make more informed and strategic decisions to reduce their costs of capital and improve their competitiveness.

5. CONCLUSION

The main objective of this study is to analyse the association between physical risk management and the cost of capital for non-financial companies in the US market. Using a sample of 1430 unique American companies, divided into 10 industrial sectors and evaluated over the period from 2021 to 2023, the study uses Moody's ESG-Physical Risk Management score to evaluate how physical risk management influences the cost of capital, including the weighted average cost of capital, the cost of equity and the cost of debt.

The results indicate a positive and significant relationship between physical risk and both WACC and cost of equity. This suggests that physical risk above the industry average is generally viewed unfavourably by investors. They may interpret these risks as signals of potential additional risk, which can lead to inefficiencies and increased risk. As a result, maintaining physical risk management practices in line with industry norms can be crucial to effectively managing the costs of both equity and overall capital. From an economic perspective, this implies that companies must adequately invest in physical risk mitigation to keep capital costs low and improve their market competitiveness.

Regarding the cost of debt (COD), the results are inconclusive. The coefficient of physical risk is not significant, suggesting that lenders do not penalize physical risk with the same intensity as equity investors. This may indicate that lenders place more emphasis on other financial and collateral parameters, rather than physical risk management. The relationship between physical risk and COD is unclear and requires further investigation to be better understood.

Performing this robustness test allows us to isolate the impact of physical risk management. By excluding Physical Risk, the potential for multicollinearity, that can obscure the true effects on financial outcomes, was reduced. This ensures that the results on the impact of physical risk are not confounded with other variables. Analysing the company's physical risk management relative to its industry provides a crucial baseline perspective for understanding competitive positioning. This helps to identify whether it is deviation from industry norms that is driving cost implications rather than absolute levels of physical risk management.

Strategically, companies can use these insights to align their physical risk management approaches more closely with industry standards, thereby potentially reducing their capital costs. Understanding that significant deviations from the norm can lead to higher required returns can guide better investment and operational decisions.

This work takes advantage of using a physical risk management score recently developed by Moody's, which offers a more detailed and accurate assessment than previous methods. Past studies have used a variety of methods to measure physical risk, such as textual analysis of annual reports and earnings calls, or using proprietary models to quantify exposure to climate risk. However, these methods had significant limitations in terms of accuracy and data availability. The approach adopted in this study, however, benefits from more robust data and an evaluation methodology developed specifically to measure physical risk management, thus offering a significant contribution to the existing literature.

Limitations of this study include the relatively limited number of years for which Moody's score is available, which could affect the generalizability of the results. Furthermore, regression models could be improved with the inclusion of new variables that could better capture the complexity of the relationship between physical risk and the cost of capital.

For future research, it would be interesting to further explore how different measures of physical risk influence the relationship with the cost of capital and build a more comprehensive theoretical framework contributing to a better understanding of how physical risk impacts the cost of capital. Further research could also focus on how business cycles influence the impact of physical risk on the cost of capital, providing a more comprehensive view of these dynamics over time. Moreover, it would be useful to investigate non-linearities in these relationships, as current studies are scarce in this area.

In conclusion, this study provides an important contribution to the understanding of physical risk management and its impact on the cost of capital, paving the way for further research and offering valuable practical insights for companies and policy makers.

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APPENDICES

APPENDIX I SAMPLE COMPOSITION BY INDUSTRY

	N	Percentage (%)	Cumulative
Academic & Educational Services	3	0.15	0.15
Basic Materials	112	5.48	5.63
Consumer Cyclicals	277	13.55	19.18
Consumer Non-Cyclicals	116	5.68	24.85
Energy	135	6.60	31.46
Healthcare	446	21.82	53.28
Industrials	297	14.53	67.81
Real Estate	153	7.49	75.29
Technology	436	21.33	96.62
Utilities	69	3.38	100.00
Total	2044	100.00	

APPENDIX II MODELS VARIABLES DEFINITION

	Dependent variables	
WACC	Implied WACC computed by Refinitiv	Refinitiv
Cost of Equity	Implied cost of equity computed by Refinitiv	Refinitiv
Cost of Debt	Implied cost of debt computed by Refinitiv	Refinitiv
	Explanatory variables	
Physical_Risk	Physical Risk score obtained from Moody's Orbit	Moody'S Orbit
IndDev	Physical Risk minus Industry-Year Median value	Author
SqrDev	Square of IndDev measure	Author
	Control variables	
Beta	Obtained from Refinitiv	Refinitiv
Size	Obtained from Refinitiv	Refinitiv
Book to Market (*BTM*)	Book to market ratio computed as (book value of equity /market value of equity)	Fama and French (1993),
Leverage (*Lev*)	Total debt/total assets	Goncalves et al (2020)
Tobin Q	(Market value + total debt)/total assets	Goncalves et al (2020)
Performance (*Perf*)	Income before extraordinary items/sales	La Rosa et al. (2018)
Tangibility (*Tang*)	Property, plant and equipment/total assets	Goncalves et al (2020)
Operating Cash Flow (*OCF*)	Operating cash flow/total assets	Goncalves et al (2020)
Industry	Industry dummy variable	
Year	Year dummy variable	

APPENDIX III PEARSON CORRELATION MATRIX

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) WACC	1.000											
(2) Cost of Equity	0.876*	1.000										
(3) Cost of Debt	0.362*	0.009	1.000									
(4) Physical Risk	-0.015	-0.021	0.012	1.000								
(5) Beta	0.166*	0.203*	0.036	0.070*	1.000							
(6) Size	0.363*	0.413*	-0.028	-0.295*	-0.008	1.000						
(7) Book to Market	-0.057*	-0.032	-0.024	-0.032	0.023	-0.048*	1.000					
(8) Leverage	0.185*	0.182*	0.061*	-0.052*	0.078*	0.261*	-0.192*	1.000				
(9) TobinQ	-0.084*	-0.100*	0.000	0.101*	-0.051*	-0.295*	-0.366*	-0.028	1.000			
(10) Performance	0.152*	0.160*	-0.015	-0.057*	0.019	0.239*	0.001	0.115*	-0.129*	1.000		
(11) Tangibility	0.104*	0.117*	0.027	-0.052*	0.096*	0.172*	0.133*	0.246*	-0.137*	0.089*	1.000	
(12) Operating Cashflow	0.230*	0.252*	-0.066*	-0.134*	0.018	0.580*	-0.022	0.084*	-0.250*	0.378*	0.174*	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

DISCLAIMER

This master thesis/internship report/project was developed with strict adherence to the academic integrity policies and guidelines set forth by ISEG, Universidade de Lisboa. The work presented herein is the result of my own research, analysis, and writing, unless otherwise cited. In the interest of transparency, I provide the following disclosure regarding the use of artificial intelligence (AI) tools in the creation of this thesis:

> I disclose that AI tools were employed during the development of this thesis as follows:
>
> - AI-based research tools were used to assist in literature review and data collection.
> - AI-powered software was utilized for data analysis and visualization.
> - Generative AI tools were consulted for brainstorming and outlining purposes. However, all final writing, synthesis, and critical analysis are my own work. Instances where AI contributions were significant are clearly cited and acknowledged.

Nonetheless, I have ensured that the use of AI tools did not compromise the originality and integrity of my work. All sources of information, whether traditional or AI-assisted, have been appropriately cited in accordance with academic standards. The ethical use of AI in research and writing has been a guiding principle throughout the preparation of this thesis.

I understand the importance of maintaining academic integrity and take full responsibility for the content and originality of this work.

Nicolò Giovanni Rizzo – 30/06/2024